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Diana Gutierrez-Posada, Tasos Kitsos, Max Nathan & Massimiliano Nuccio

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Creative Clusters and Creative Multipliers: Evidence from UK Cities

Diana Gutierrez-Posada
REGIOlab
University of Oviedo
Oviedo 33003
Spain
gutierrezdiana@uniovi.es

Tasos Kitsos
Department of Economics, Finance and Entrepreneurship
Aston Business School
Birmingham B4 7ET
UK
a.kitsos@aston.ac.uk

Max Nathan
Centre for Advanced Spatial Analysis
University College London
London WC1E 6BT
UK
max.nathan@ucl.ac.uk
and
Centre for Economic Performance (CEP)
London School of Economics
London WC2A 2AE
UK

Massimiliano Nuccio
Department for Management
Università Ca' Foscari Venezia
30123 Venice
Italy
massimiliano.nuccio@unive.it

abstract

Economic geographers have paid much attention to the cultural and creative industries, both for their propensity to cluster in urban settings, and their potential to drive urban economic development. However, evidence on the latter is surprisingly sparse. In this article, we explore the long-term, causal impacts of the cultural and creative industries on surrounding urban economies. Adapting Moretti's local multipliers framework, we build a new twenty-year panel of UK cities, using historical instruments to identify causal effects of creative activity on noncreative firms and employment. We find that each creative job generates at least 1.9 nontradable jobs between 1998 and 2018. Prior to 2007, these effects seem more rooted in creative services employees' local spending than visitors to creative amenities. Given the low numbers of creative jobs in most cities, the overall impact of the creative multiplier is small. On average, the creative sector is responsible for over 16 percent of nontradable job growth in our sample, though impacts will be larger in bigger clusters. We do not find the same effects for workplaces, and we find no causal evidence for spillovers from creative activity to other tradable sectors. In turn, this implies that creative city policies will have partial, uneven local economic impacts. Given extensive urban clusters of creative activity in many countries, our results hold value beyond the UK setting.

Key words:
creative industries
local multipliers
cities
local economic development

JEL codes:
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O18
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This article tests the causal impacts of the creative and cultural industries on surrounding urban economies, specifically on noncreative jobs and firms. Economic geographers have extensively studied the creative and cultural industries (Scott 1988; Zukin 1995; Hall 1998; Throsby 2001; Florida 2005; Cooke and Lazzeretti 2008; Hutton 2008; Boschma and Fritsch 2009; Mould 2015; Van Damme, De Munck, and Miles 2017). There are two broad reasons for this. First, these sectors are highly clustered[1] in a few urban locations (Hesmondhalgh 2012; Bloom et al. 2020). In the UK, for example, 53 percent of creative industries jobs and 44 percent of firms are found in just five cities (Mateos-Garcia, Klinger, and Stathoulopoulos 2018), and this concentration is increasing over time (Tether 2019). Second, cultural and creative industries are also viewed as drivers of urban economic development: creative work is seen as highly skilled, often high value added, and with spillover effects on the wider area (Florida 2005; Boschma and Fritsch 2009; Marrocu and Paci 2012).[2] If the creative industries *do* have this urban growth potential, however, their unevenness may generate significant—and lasting—economic disparities across the wider urban system.

There is a large literature describing urban creative clusters across countries (Lazzeretti, Boix, and Capone 2008; de Vaan, Boschma, and Frenken 2013; Boix et al. 2014; Kemeny, Nathan, and O'Brien 2020), within countries (Bertacchini and Borrione 2013; Alfken, Broekel, and Sternberg 2015; Nuccio and Ponzini 2017; Mateos-Garcia, Klinger, and Stathoulopoulos 2018; Tao et al. 2019) and within cities (Catungal, Leslie, and Hii 2009; O'Connor and Gu 2014; Hracs 2015). However, the impact—if any—of such clusters on local economies is less well understood and is the focus of our article.

Creative clustering may simply reflect shifts toward knowledge-based economies (Zukin 1995; Scott 2006; Pratt and Jeffcut 2009) and the benefits of big city location (Hall 2000; Hutton 2008). However, clusters could also generate halo effects

[1]We use colocated, concentrated, and clustered synonymously.
[2]We use cultural and creative and creative industries interchangeably. We discuss terms further in "Theoretical Framework."

this work does not imply the endorsement of the ONS or the Secure Data Service at the UK Data Archive in relation to the interpretation or analysis of the data. This work uses research data sets that may not exactly reproduce National Statistics aggregates. All the outputs have been granted final clearance by the staff of the SDS-UKDA. This article represents the views of the authors, not the funders or the data providers.

on other sectors and/or displace other activities. Benefits might arise through higher local worker/visitor spending, improved local supply chains, and knowledge spillovers (Bakhshi and McVittie 2009; Lee 2014). Conversely, clusters might displace other industries, a process of industrial gentrification (Yoon and Currid-Halkett 2014). These impacts may vary substantively over the business cycle, and may also differ extensively *within* the creative industries, given the differences between (say) advertising and the arts. The empirical base for these wider impacts is inconclusive. Most evidence draws on single case studies, or is constrained by short time periods or problematic research designs, or both of these. (Bloom et al. 2020).[3]

At first glance, creative spillovers are indeed at work in UK cities: Figure 1 plots the log change in urban creative industries jobs between 1998 and 2018, per UK official industry definitions, against the log change in local services (nontradables such as retail and leisure) over the same period. We cannot be sure that the creative industries drive this positive relationship: wealthier cities could have simply developed more creative activity and more local services.

Our article thus aims to identify the causal impacts of urban creative activity on jobs and firms in urban nontradable and other tradable industries. We build a new twenty-year panel of UK cities using rich microdata. Adapting Moretti's (2010) local multipliers framework, we estimate short- and long-term cumulative impacts from 1998 to 2018, using historic instruments—plus weak instrument-robust inference—to identify causal effects.

We have four main results. First, creative activity progressively concentrates in a small number of cities, though with diffusion across the biggest clusters. Second, we find robust, positive employment impacts of creative industries on urban local services. Taken together, this means that job multipliers are large, but overall effects are uneven: each creative job generates at least 1.96 nontradable jobs over our twenty-year period, or 16.4 percent of nontradable

[3]We discuss this literature in more detail in "Theoretical Framework."

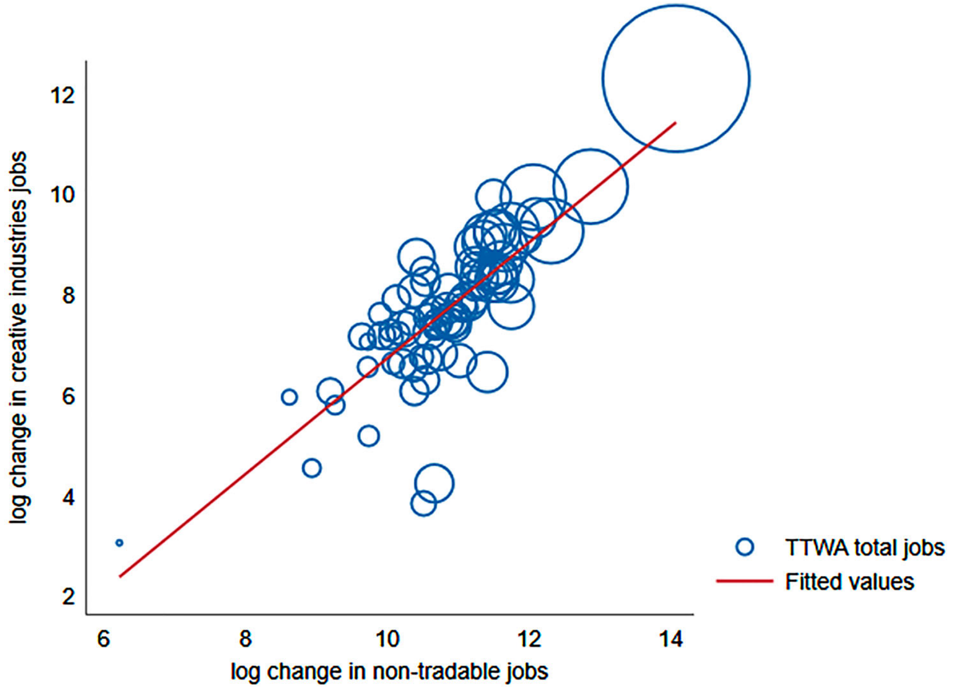

Figure 1. Change in creative vs. nontradable jobs, urban TTWAs, 1998–2018.
Note: Plot shows correlation between log change and in nontradeable jobs (x axis) and creative industries jobs (y axis). Creative industries and nontradeables defined as in "Data."
Source: Business Structure Database (BSD) (Office for National Statistics 2019). Seventy-eight urban TTWAs weighted by number of workplaces.

job growth in the average Travel to Work Area (TTWA) in that period. For workplaces, we find no similar effects, and job multipliers decline substantially after the 2007 financial crisis. Third, impacts on local services reflect both creative workers' spending and visitors to urban amenities, such as galleries and museums, although the former is stronger than the latter. Fourth, we find weak, suggestive evidence of spillovers from creative industries to activity in other tradable sectors.

The article makes multiple contributions to both current debates in economic geography and the cultural and creative industries literature. Our findings contribute to the fundamental questions on city growth and the economic foundations and trajectories of postindustrial cities in which creativity is often presented as an economic driving force (Zukin 1995; Hall 1998; Florida 2002; Scott 2006; Hutton 2015). Given similar trends in creative clustering in other more developed countries, our results have resonance beyond the UK setting. We widen the horizon of existing creative industries analysis via a robust research design, high-quality granular data, and a long time frame, all issues flagged by Bloom et al. (2020) in their review of the field. We also tackle broader empirical limitations in the local multipliers literature, notably arbitrary time periods and overly aggregated sectoral definitions (Osman and Kemeny 2021).

Our results also hold important lessons for urban economic development policy, specifically the effective reach of *creative city* programs, where the creative economy is often assumed to have extensive local upsides and no downsides (Mathews 2010; Lindner 2018). Our results suggest creative economy-led policies can have positive local economic impacts, but they are subject to important spatial and sectoral constraints.

The rest of the article runs as follows. The next section outlines our conceptual framework and reviews the empirical literature. This is followed by a section describing data and build. Following that is a section that provides descriptive evidence and a section that outlines our research design. The next two sections present main results and extensions. Finally, the last section summarizes findings, discusses policy implications, and identifies areas for further work.

Theoretical Framework

Defining the Creative Industries

The cultural and creative industries "supply goods and services that we broadly associate with cultural, artistic, or simply entertainment value" (Caves 2002), 1). These are now taken to include the visual and performing arts; heritage; and cultural industries such as cinema, design, TV, fashion, and computer games. Cultural products and services typically combine artistic and humdrum inputs, involving a wide range of skill sets and short time frames (Caves 2002); given winner-takes-all effects, creative industries make heavy use of contingent, project-based working and options-based contracts, with the largest firms focused on packaging and distribution over production. Creative workers perform highly skilled roles rich in problem solving, using novel processes involving a high share of nonrepetitive tasks and resistant to mechanization (Bakhshi, Freeman, and Higgs 2012). Nevertheless, labor force conditions vary widely in creative sectors, with a large minority of well-paid, secure positions in creative services such as advertising, architecture, software and the media, and an overrepresentation of insecure self-employment/portfolio working, especially in the arts (Brook, O'Brien, and Taylor 2020).

The accepted set of cultural and creative industries has broadened over time: from the arts, to a larger set of cultural products and services, and most recently to a wider set of activities with a critical mass of creative activity (Flew 2002; Hesmondhalgh 2012).[4] As set out in "Data," our industry definitions are also based on this most recent creative intensity framework (Bakhshi, Freeman, and Higgs 2012). Cultural and creative industries are now seen as part of larger shifts toward service- and knowledge-based economies, in which creativity is an important input, and consumption is a means of expressing identity: what Lash and Urry (1984) call culturalization and what Scott (2014) dubs *cognitive-cultural capitalism*. This broader creative industry space is also closely linked to urban change and the growth of creative clusters in postindustrial cities.

The Urban Economic Impacts of Creative Activity

The urban footprint of creative industries naturally raises questions about effects on their surroundings. A first view is that urbanized creative industries are simply the spatial manifestation of a culturalized postindustrial economy. While creative embedding might

[4]Hesmondhalgh (2012) distinguishes between *cultural industries* as a term of positive analysis, and *creative industries* as a normative policy concept embodying strong claims about creativity's economic importance.

differ across countries (Boix et al. 2014; Kemeny, Nathan, and O'Brien 2020), creative clusters have no *necessary* wider local impact. Rather, creative firms colocate in postindustrial cities because they benefit from agglomeration economies and other urban affordances (Scott 1988; Zukin 1995; Hall 1998, 2000).

A contrasting view is that creative industries do have important local multiplier effects. High-paid creative service workers' spending may support job growth and firm creation in local services like cafes, bars, and shops (Hutton 2008; Lee 2014). In parallel, arts, heritage, and museums can be powerful attractors for both residents and tourists, with similar local spending effects (Florida 2002; Pratt and Jeffcut 2009). Creative actors' interactions with noncreative sectors may also amplify urban agglomeration economies (Duranton and Puga (2004). For example, creative industries might add value through supply chain linkages (Bakhshi and McVittie 2009), or by adding to the stock of ideas in a city, raising innovation and productivity (Müller, Rammer, and Trüby 2009; Pratt and Jeffcut 2009; Boix-Domenech and Soler-Marco 2017).

A third view is that causality runs both ways. Creative industries activity, especially in creative business services, is highly procyclical (Stam, De Jong, and Marlet 2008). If wealthier and more productive cities have larger creative economies, this may reflect local demand from other industries and households as well as creative multipliers (Hall 2000; Marco-Serrano, Rausell-Koster, and Abeledo-Sanchis 2014).

Moretti's seminal work (2010) offers a way to formalize these perspectives. The base case is a *growth shock* to a city's tradable activities (that is, goods and services that can be both consumed locally and exported to other locations). A creative industries growth shock might come through a major relocation, or through longer-term structural shifts like culturalization: Moretti and Thulin (2013) emphasize the role of deeper shifts in consumer preferences (such as for urban amenities and experiences).

The shock directly increases creative activity and may also have indirect effects. First, we may see multiplier effects on nontradable activity (that is, services such as retail and leisure that are provided and consumed locally). Second, there may be multiplier effects on other tradable sectors, via supply chain links, knowledge spillovers, or both: these vary with the extent of (1) cross-industry spillovers versus (2) competition for inputs. Third, we may see these effects on the intensive margin (more jobs in existing noncreative firms) and/or the extensive margin (more noncreative firms).

Estimating multipliers *within* creative industries subgroups helps pin down mechanisms. Creative services, especially knowledge-intensive business services have (at least some) highly paid workers. As such, multipliers from creative services on nontradable activity are likely to derive from worker spending. By contrast, the lower-wage structure of employment in music, museums, art galleries, and crafts implies that multipliers on nontradables are more likely to derive from the value of urban amenities and related visitor expenditure.

Existing Evidence

This basic framework allows local multipliers and their drivers to be directly estimated, and a growing body of employment multiplier studies has developed since 2010. Van Dijk (2018) develops a detailed critique of Moretti's original implementation, suggesting several modifications that we draw on below. In a recent OECD-wide review of the field (What Works Centre for Local Economic Growth 2019), each additional job in the tradable sector generates on average 0.9 additional jobs in the untraded sector: skilled/high-tech activities have higher multipliers, averaging 2.5 and 1.9 additional non-tradable jobs, respectively. However, none of these studies look at creative activity.

A number of other articles do look at urban and regional impacts of the creative industries but typically use short sample periods (under ten years), and none look at mechanisms in detail (e.g., the role of arts vs. creative services). Several articles also use shift-share instruments, an approach we suggest has serious drawbacks in the creative industries case (see "Research Design"). Boix-Domenench and Soler-Marco (2017) use a Generalised Method of Moments estimator to test links between creative services presence and labor productivity for 250 EU regions in 2008, finding a positive effect. Boix, De-Miguel-Molina, and Hervas-Oliver (2013) also find positive links between creative services and wealth in EU regions in 2008, using a shift-share instrument. Conversely, Marco-Serrano, Rausell-Koster, and Abeledo-Sanchis (2014) explore creative industry—gross domestic product links for EU regions between 1999 and 2008, finding clear, both ways, causation in a Structural Equation Model estimator. For UK cities, Lee (2014) uses a shift-share instrument to explore links between creative industries employment and overall urban wages/employment between 2003 and 2008, finding positive wage links but no effect on jobs. Our closest comparator is Lee and Clarke (2017), who run a Moretti-style analysis for 2009–15 with a shift-share instrument, again finding no evidence of creative employment multipliers.

Other studies test for associations rather than causal effects. For example, Rodríguez-Pose and Lee (2020) find that it is the simultaneous presence of creative and science, technology, engineering, and mathematics workers that is associated with the highest patenting growth in US cities. In the UK, Lee and Rodríguez-Pose (2014) find that businesses in cities with high rates of creative businesses tend to be more innovative while Innocenti and Lazaretti (2019), studying Italian provinces, suggest that the co-location of creative industries and other closely related sectors is necessary to observe positive employment spillover effects. Stam, De Jong, and Marlet (2008) show positive associations between creative industries presence and job growth in Amsterdam, but not in other Dutch cities.

Data

Our main data source is the Business Structure Database (BSD) (Office for National Statistics 2019). The BSD covers over 99 percent of all UK economic activities and provides reliable information for individual workplaces (plants) and jobs by sector. After extensive cleaning, detailed in Appendix A1 in the online material, we aggregate workplace-level information to 2011 Travel to Work Areas (TTWAs), city-regional geographies that provide the best available approximation for spatial economies. Of the 228 TTWAs, we focus on 78 that are predominantly urban, following Gibbons, Overman, and Resende (2011). Our panel has 1,716 urban TTWA-year observations for twenty-two years, 1997–2018 inclusive. (Note that the BSD does not include freelancers or self-employed workers with revenues below the UK sales tax threshold.[5] Freelancing

[5]Currently £85,000 per year, or US$106,300 (as of June 2022).

and self-employment are common in the creative industries, so our raw data likely undercounts true levels of creative activity. (See "Inference" for further discussion.)

We then build our key variables according to the ideas developed in "Theoretical Framework." We first decompose industries into tradable and nontradable components. Tradable space includes creative industries plus manufacturing and tradable services.[6] Nontradable space includes public-sector activities, such as education and health care, and nontradable services, such as retail, leisure, and hospitality.

We define creative and cultural industries using the UK's official creative industries definition (Department for Digital, Culture, Media and Sport [DCMS] 2018), using crosswalks to make time-consistent sector codes for nine subgroups: advertising and marketing; architecture; crafts; design; film, TV, video, radio and photography; information technology (IT), software, and computer services; publishing; museums, galleries, and libraries; music, performing and visual arts.

Manufacturing and public-sector activities are defined per Faggio and Overman (2014). To identify tradable and nontradable services, we use locational Gini coefficients as developed in Jensen et al. (2005) and widely used in this literature. We build new locational Ginis for detailed four-digit UK industries based on 2018 BSD data. See Appendix A2 in the online material for details. For control variables and robustness checks, we use microdata from the Annual Population Survey (APS) (Office for National Statistics Social Survey Division 2019), Labour Force Survey (LFS) (Office for National Statistics Social Survey Division and Northern Ireland Statistics and Research Agency Central Survey Unit 2019), and information from other UK Office of National Statistics (ONS) data sets covering population, GVA per head, and household disposable income. As before, all data sets are aggregated to TTWA level. Further details are given in "Research Design" and "Results."

Descriptive Analysis

How has urban creative activity evolved over time, and across cities? Table 1 gives summary statistics for 1998–2018 (Panel A), 1998 (Panel B) and 2018 (Panel C). Alongside substantial increases in overall economic activity, the average urban TTWA in 2018 has more creative activity than 1998, and this accounts for a larger share of local economic activity.

This aggregate picture hides much spatial variation. First, only a few cities drive overall rises. Figure 2 is a kernel density distribution showing urban TTWAs' local shares of creative workplaces/firms (left-hand side) and employment (right-hand side) in 1998 (blue) and 2018 (red). Most areas have very low shares. Local shares of creative activity grow but with the biggest shifts at the top of the distribution. These patterns are consistent with other UK work by Mateos-Garcia, Klinger, and Stathoulopoulos (2018) and Tether (2019) as well as the broader cross-country literature discussed in the introduction to this article.

Second, patterns of creative specialization suggest both clustering *and* diffusion. Figure 3 shows the distribution of location quotients (LQs) for creative firms (left-hand

[6]Some creative industries subgroups—notably crafts, museums, galleries, and libraries—are arguably nontradable. Overall, they represent under 7 percent of total creative industries gross value added (GVA) (DCMS 2018). For this analysis, we allocate them to tradable space.

Table 1

Summary Statistics

	A. All Years		B. 1998		C. 2018	
	Mean	sd	Mean	sd	Mean	sd
TTWA all workplaces	22433	43798	19846	37959	28790	61437
TTWA tradables workplaces	6380	15663	5364	12758	8608	22802
TTWA creative workplaces	2146	6580	1721	5151	3153	9961
TTWA other tradable workplaces	4233	9128	3643	7651	5455	12882
TTWA nontradable workplaces	16054	28225	14482	25255	20181	38760
% tradable workplaces/all workplaces	0.284	0.042	0.27	0.041	0.299	0.047
% creative workplaces/all workplaces	0.095	0.03	0.087	0.03	0.11	0.033
% other tradable workplaces/workplaces	0.189	0.021	0.184	0.022	0.189	0.02
% nontradable workplaces/all workplaces	0.716	0.042	0.73	0.041	0.701	0.047
TTWA all jobs	252793	455899	223984	406268	307218	586922
TTWA tradables jobs	64513	129808	68314	131554	71997	163951
TTWA creative jobs	11396	37242	8870	28537	15513	53646
TTWA other tradable jobs	53118	93580	59444	103773	56484	110968
TTWA nontradable jobs	188279	327061	155670	275172	235220	423705
% tradable jobs/all jobs	0.255	0.051	0.305	0.05	0.234	0.037
% creative jobs/all jobs	0.045	0.017	0.039	0.015	0.05	0.018
% other tradable jobs/all jobs	0.21	0.052	0.265	0.053	0.184	0.034
% nontradable jobs/all jobs	0.745	0.051	0.695	0.05	0.766	0.037
*TTWA*year observations*	*1638*		*78*		*78*	

Source: BSD.

side) and jobs (right-hand side) in 1998 and in 2018. An LQ over one indicates an industry is more concentrated in an area than its national share, indicating clustering. As shown by the grey veritcals, only a minority of cities have LQs over one. On both workplaces and jobs measures, overall distributions have become more extreme. Creative job specialization has risen at the very top of the distribution but fallen in other clusters; workplace specialization has diffused in all clusters.

This spatial and time persistence has important implications for our regression analysis as we discuss in "Research Design." Nevertheless, some individual cities have shifted position in the creative cluster league table. Appendix Tables B1–B3 in the online material give more detail for the twenty urban TTWAs with the largest initial creative industries counts, shares, and LQs, respectively. Not surprisingly, London and its wider megaregion (including Slough, Guildford, Luton, and Reading) dominates in creative firm and employment counts. Outside mega-London, other major cities with large counts include Manchester, Birmingham, Bristol, and Cambridge. The picture is broadly similar for shares, although compared to smaller, more specialized cities, such as Reading, Slough, and Milton Keynes, by 2018 London has a lower local share of creative activity. All of the biggest clusters have lower workplace LQs in 2018 than 1998, with Edinburgh emerging as a top twenty cluster in 2018. For jobs LQs, Luton, Crawley, and Tunbridge Wells have technically declustered between 1998 and 2018; in contrast, Bristol has emerged as a cluster for both creative workplaces and employment.

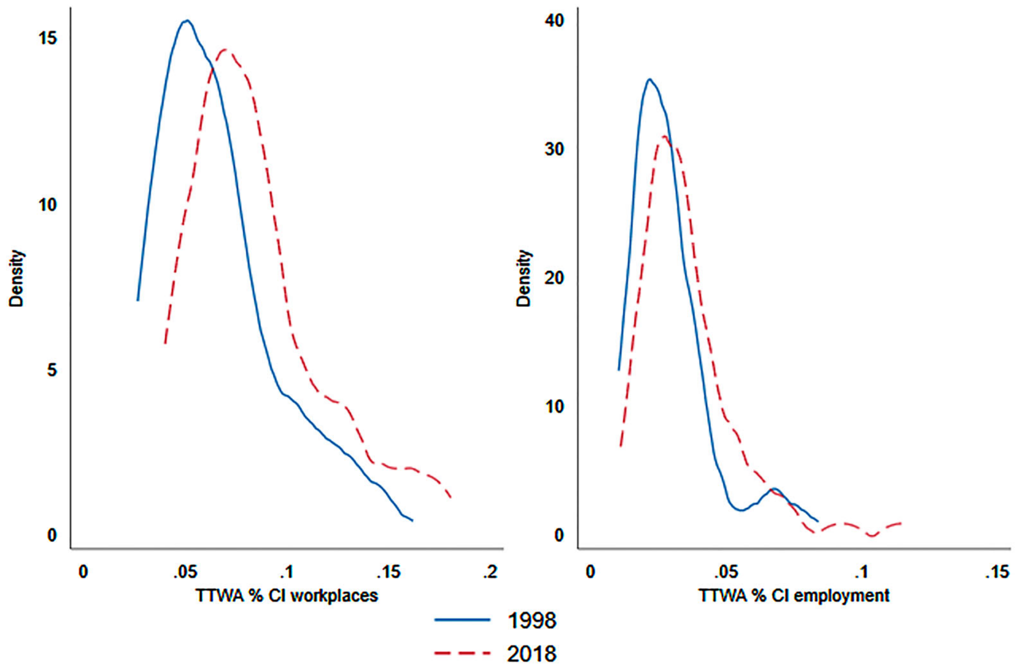

Figure 2. Kernel density plot of percentage creative industries workplaces and employment, urban TTWAs, 1998 and 2018.
Note: Pilots show distribution of creative industries workplaces (left) and employment (right) as a share of all TTWA workplaces/employment.
Source: BSD. Epanechnikov kernel for 78 urban TTWAs.

Research Design

We now take our framework formally to the data. Per "Theoretical Framework," to explore causal links from creative industries activity to noncreative activity, we start with the following ordinary least squares (OLS) fixed effects regression for TTWA i in year t

$$ln(\mathrm{NT})_{it} = a + b1ln(\mathrm{CI})_{it} + b2ln(\mathrm{OT})_{it} + \mathbf{X}c_{it-n} + \mathrm{I}_i + \mathrm{T}_t + e_{it} \qquad (1)$$

where NT, CI, and OT are, respectively, activity counts in nontradable, creative industries, and other tradable sectors, as defined in "Data"; **X** is a vector of controls lagged n years ($n = 1$, varied in robustness checks), and I and T are area and year fixed effects. Our variable of interest is CI, where $b1$ is the elasticity of nontradable activity to CI activity. We interpret this as the percentage change in nontradable activity from a 1 percent change in creative industry activity. Following our theoretical framework, we are interested in impacts on both the intensive margin (more jobs) and the extensive margin (more firms). We estimate (1) in levels for 1998–2018, and for start and end years only, equivalent to the long differences approach in Moretti (2010) and Lee and Clarke (2019). We run alternative specifications for both settings in robustness checks. To cover the full UK business cycle, we estimate for the subperiods 1998–2006 and 2007–2018

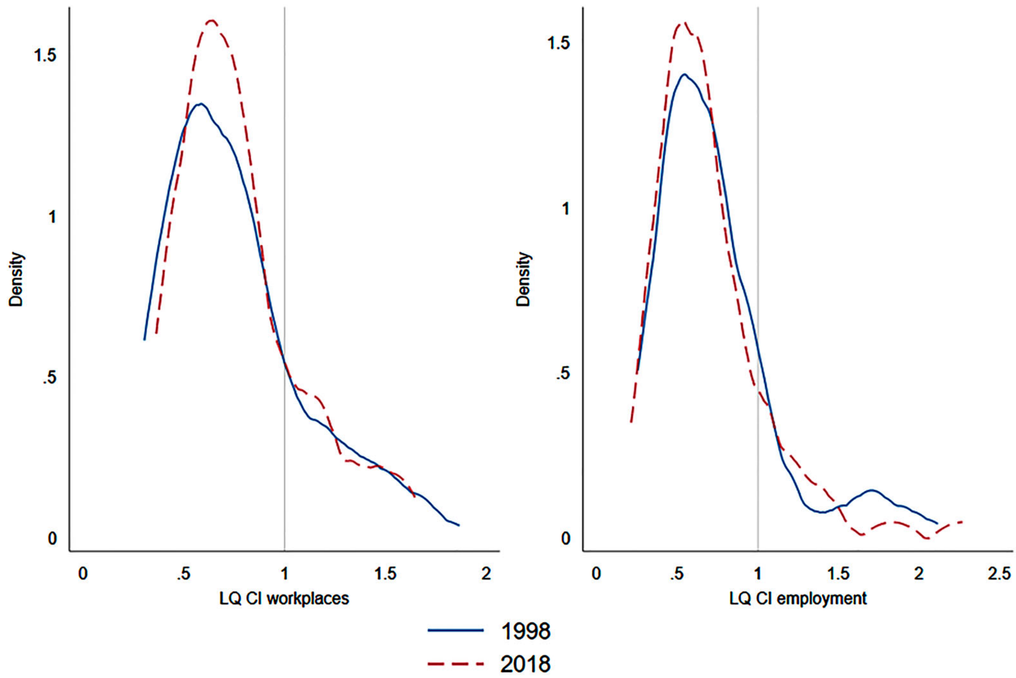

Figure 3. Kernel density plot of creative industries workplaces and employment LQs, urban TTWAs, 1998 and 2018.
Note: Pilots show distribution of LQs for creative industries workplaces (left) and employment (right).
Source: BSD. Epanechnikov kernel for 78 urban TTWAs.

(broadly, pre- and post–Great Financial Crisis). In extensions, we also look within creative subgroups and at impacts on other tradables.

We then calculate multipliers, where M gives the number of additional nontradable jobs (or workplaces) arising from one extra creative job (or workplace)

$$M = \widehat{b1} *(NT_{2007}/CI_{2007}) \quad (2)$$

where $\widehat{b1}$ is the estimated coefficient from (1), NT_{2007} is the sum of nontradable jobs or workplaces in 2007 across TTWAs, and CI_{2007} gives the same for creative industries in 2007. We also calculate an alternative specification following Van Dijk (2018), using both 1998 and 2007 as base years to better follow labor market time trends.

Identification

Our panel estimators handle time-fixed area characteristics and cross-area shocks in a given year. Urban creative activity is also influenced by time-varying skills and tastes of the workforce and population, agglomeration economies, and local labor market conditions. We therefore control for one-period lags of the share of graduate residents in a TTWA and the TTWA's International Labor Organization unemployment rate (from APS and LFS data), plus population density and the share of sixteen to twenty-four-year-olds in the city (from ONS midyear population estimates). In robustness checks, we vary these controls and lag structure.

Our base regressions may also suffer from simultaneity or reverse causation between creative and nontradable activity. Lacking a natural experiment, we turn to instrumental variables (IVs). The multipliers literature typically uses shift-share instruments (Osman and Kemeny 2021).[7] Several recent studies critically evaluate such instruments (Broxterman and Larson 2020; Cerqua and Pellegrini 2020). If national shifts are not as-good-as-random, the instrument will not be identified (Borusyak, Hull, and Jaravel 2022). If local shares are serially correlated, the instrument also fails, since it incorporates past and current demand shocks (Goldsmith-Pinkham, Sorkin, and Swift 2018; Jaeger, Ruist, and Stuhler 2018). Per "Descriptive Analysis," UK creative industries are highly clustered, and this persists over time. Further, there has been no large national shock to creative industries in our sample period. It is thus unlikely that shift-share instruments can convincingly identify causal effects of creative industries in the UK. Our alternative approach is to use historical instruments, exploiting the long-term effects of industrial structure and supporting institutions.[8]

Our first instrument builds on Chinitz (1961), who argues that cities historically dominated by small firms and small and medium-sized enterprises have persistently stronger entrepreneurial cultures today. We argue that these dynamics also apply to creative industries, which have notably larger-than-average shares of microfirms and self-employment.[9] Thus, cities historically dependent on single-industry, large-firm dominance should also have less *creative* activity today. To proxy for this dependence, we use cities' proximity to nineteenth-century mining deposits, an exogenous feature used successfully to predict entrepreneurial activity in the US (Glaeser, Pekkala Kerr, and Kerr 2015) and the UK (Stuetzer et al. 2016). Our instrument is the log distance from a TTWA centroid to the nearest historic active coalfield. We expect to see a positive link from distance to creative industries activity.

Our second instrument builds on the idea that historical cultural institutions make a long-term impact on local cultural clusters today (Falck, Fritsch, and Heblich 2011). Specifically, we use historic schools of art and design established in the Victorian and Edwardian eras, 1837–1914 (Lee and Clarke 2019). The first Government School of Design opened in London in 1837; in subsequent years, such schools flourished in many industrial cities (Lawrence 2014), offering urban working-class children the opportunity to learn engineering and chemistry alongside then-new creative technologies related to design, photography, film, and printing. We argue such historic institutions helped root creative cluster by supplying skilled workers to local firms, as a

[7]See Boix, De-Miguel-Molina, and Hervas-Oliver (2013), Moretti and Thulin (2013), Lee (2014), Van Dijk (2018), Lee and Clarke (2019), and Osman and Kemeny (2021) for recent examples.

[8]For completeness we also construct a shift-share instrument using a leave-one-out design (see Appendix A3 for details in the online material). We use this to (1) benchmark our main estimates and (2) estimate impacts from tradables to nontradables since identifying assumptions are better founded here.

[9]In 2017, the creative industries had 95 percent microfirms and 0.14 percent large firms, vs. 89 percent and 0.37 percent, respectively, across all industries (Business Register and Employment Survey data, accessed via www.nomisweb.co.uk). In 2015, over 26 percent of creative industries workers were self-employed, versus 16 percent of all UK workers (DCMS Sectors Economic Estimates, via https://tinyurl.com/ycfx47hr).

source of ideas, and through two-way linkages between teaching staff and local firms. Our list includes both London (fifteen of fifty-two schools) and major cities but also ex-industrial and more peripheral locations. Our instrument is the count of historic art and design schools in TTWA, and we expect to see a positive connection from the count to creative activity today.

For these instruments to be valid, they must only directly affect creative industries activity and leave nontradable activity unaffected (except through changes in creative activity). Table 2 shows results of a diagnostic regression of our instruments on employment (Panel A) and workplaces (Panel B) in our different industry groupings. For each panel we show results for creative industries (column 1), nontradables (column 2), and other tradables (column 3).

Encouragingly, we find the expected positive links for the coalfields instrument to creative employment and workplaces, and we find no significant links to nontradable activity. We also find weak negative links from our instruments to other tradables activity. In robustness checks, we therefore treat both creative and other tradables activity as endogenous: this does not affect our main result. Where we test creative-to-other tradable linkages, we use only the art schools instrument.

Inference

Weak instruments are pervasive in the multipliers literature (Osman and Kemeny 2021). Following Osman and Kemeny, we use the weak instrument-robust methods developed by Andrews, Stock, and Sun (2019) for cases where our IVs do not pass cutoffs. The intuition is that when an instrument is valid but weak, as here, there is a set of values under which we can infer a consistent result. Specifically, the Anderson-Rubin statistic tests for the null hypothesis of instrument exogeneity for the value of

Table 2

Historical Instruments Diagnostics Tests

	A. Employment			B. Workplaces		
	(1)	(2)	(3)	(1)	(2)	(3)
log TTWA-coalfield distance	0.17***	0.01	-0.11***	0.12***	0.01	-0.03***
	(0.051)	(0.020)	(0.027)	(0.038)	(0.014)	(0.012)
TTWA frequency of art schools	0.1	0.02	-0.06*	0.02	0.01	-0.01
	(0.069)	(0.028)	(0.038)	(0.062)	(0.023)	(0.025)
Log other tradable jobs	0.13	0.60***		1.39***	0.96***	
	(0.147)	(0.045)		(0.189)	(0.071)	
Log nontradable jobs	1.06***		0.93***	-0.21		0.72***
	(0.165)		(0.096)	(0.197)		(0.049)
Log creative industries jobs		0.26***	0.05		-0.05	0.26***
		(0.040)	(0.054)		(0.049)	(0.030)
Observations	1638	1638	1638	1638	1638	1638
R^2	0.91	0.96	0.95	0.94	0.97	0.98
F-statistic	403.41	1067.61	987.32	977.97	1568.95	1926

Sources: BSD, APS, LFS, ONS data sets. All specifications include year dummies and controls per main specification. Standard errors clustered on TTWA. Constant not shown.

the point estimate $\widehat{b1}$. For an exactly identified regression, the subsequent Anderson-Rubin confidence set is the set of values for $\widehat{b1}$ for which exogeneity cannot be rejected (and this set can exist even when overall tests of instrument exogeneity fail). We use the minima of these sets to present our results as lower bounds. We do this for two reasons. First, using minima gives a more straightforward interpretation. Second, as flagged in "Data," our raw data undercounts the true numbers of creative firms and jobs.

Results

This section gives headline results. We first discuss OLS estimates, then our preferred IV regressions.

OLS Results

Figure 4 summarizes OLS results for jobs and workplaces. Each graph gives point

estimates and 95 percent confidence intervals for the variable of interest, in a fully specified model with controls and fixed effects. (Appendix Tables B4–B7 in the online material give full results for coefficients, standard errors and model fit.) Overall, we find positive associations between creative to nontradable activity, but these links are not always statistically significant and are always smaller than for other tradable sectors.

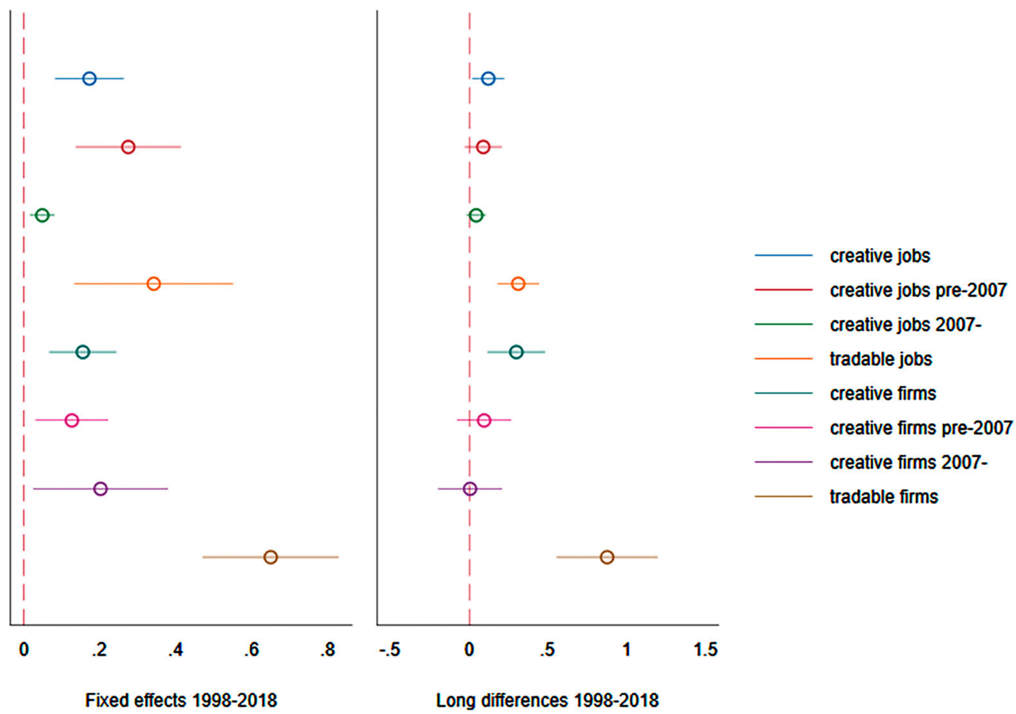

Figure 4. Plot of OLS regression of creative activity on nontradable activity.
Note: Each point shows OLS coefficient and 95 percent confidence interval. All modules use TTWA dummies, plus controls from our main specification.
Source: BSD, LFS/APS, ONS, TTWAs by year cells.

The left-hand graph shows results for the fixed effects estimator. The first three estimates show the average (noncausal) link between creative and nontradable jobs in urban areas: for 1998–2018, 1998–2006, and 2007–18, respectively. We see a significant, positive link from creative to nontradable jobs overall. Specifically, a 10 percent increase in creative employment in a TTWA is associated with 1.7 percent growth in nontradable jobs (Appendix Table B4, column 2 in the online material). This is explained by larger changes pre-2007 rather than after. The fourth estimate shows the link for all tradable activity as a benchmark: it is notably larger than the creative industries coefficients as are those for other tradables. The next four estimates repeat the analysis for workplaces (Table B5 gives full results). We find a robust positive link from creative to nontradable firms, which is now stronger from 2007.

The right-hand graph repeats these results for the long difference estimator, showing the *cumulative* link between creative and nontradable jobs/workplaces over 1998–2018, 1998–2006 and 2007–18, respectively. Here, 10 percent growth in creative jobs between 1998 and 2018 is associated with 1.2 percent growth in nontradable jobs in a TTWA (Table B6, column 2). For workplaces, the overall cumulative link is also robust (Table B7, column 2). There is not enough subperiod variation to give a significant association (Tables B6–B7, columns 2–4). Again, coefficients on (other) tradables are always larger than those for creative industries.

Robustness Checks

We run OLS results through a battery of robustness checks (Tables B8–B12 in the online material). Our first set of checks cover alternative control variables and time splits (Tables B8–B9, for our fixed effects and long difference estimators, respectively). Reassuringly, our main results are stable across these alternative specifications. Our second set of checks cover functional form. Table B10 estimates in first differences: estimates are very similar to fixed effects coefficients. Table B11 gives results for an alternative long difference model with base year controls only (a growth rate setting). For both outcomes, the coefficient of creative activity is now slightly smaller. For jobs, the coefficient is now only marginally significant, although model fit is also much lower. For workplaces, it remains robust. Table B12 fits one-period lags of creative and other tradable activity as well as lagged controls. Coefficients of creative activity fall by around 50 percent. For jobs, the result remains robust, while for workplaces it becomes marginally significant. As before, model fit also declines.

IV Results

We now turn to causal regressions with our historical instruments. As discussed in "Research Design," we estimate the *cumulative* causal impact of creative on nontradable activity in UK cities.

Tables 3 and 4 report OLS results (column 1), IV for creative industries (columns 2–4) and a benchmarking IV regression for tradable activity (column 5), for jobs and workplaces, respectively. First stage results for the instruments are in italics. Under each column, we show Montiel Olea-Pflueger Effective *F*-statistics (Andrews, Stock, and Sun 2019)

Table 3

IV Regression for Impact of Creative Employment on Nontradables. Long Difference Estimator 1998/2018.

	OLS	IV			
	(1)	(2)	(3)	(4)	(5)
Log creative industries jobs	0.12**	0.36***	0.37***	0.24***	
	(0.051)	(0.081)	(0.071)	(0.079)	
Log other tradable jobs	0.25***	0.53***	0.50***	0.62***	
	(0.066)	(0.074)	(0.068)	(0.078)	
Log tradable jobs					0.13
					(0.225)
log TTWA-coalfield distance		*0.24****	*0.26****	*0.23****	
		(0.061)	*(0.061)*	*(0.057)*	
TTWA frequency of art schools		*0.19***	*0.19***	*0.18***	
		(0.093)	*(0.093)*	*(0.081)*	
Log Bartik tradable employment					*1.42****
					(0.366)
Observations	156	156	156	156	156
R^2	0.94	0.96	0.96	0.96	0.7
Kleibergen-Paap *F*-statistic		9.52	11.33	9.66	15.15
Montiel Olea-Pflueger Effective *F*		7.465	8.71	8.944	15.15
Anderson-Rubin confidence set		[0.112, 0.620]	[0.141, 0.557]	[0.046, 0.437]	
Multiplier—Van Dijk	2.126	[1.961, 10.888]	[2.476, 9.784]	[0.797, 7.568]	0.287

Source: BSD, APS, LFS, ONS data sets.
Note: TTWA-by-year cells. All models use controls as in our main specification. Standard errors in parentheses, clustered on TTWA. * 10%, ** 5%, *** 1% significance. Confidence sets are confidence intervals around point estimates for creative industries jobs, except for column 5 (tradable jobs).

alongside a conventional weak instrument F-test. In most cases, the former scores under 10, indicating the need for weak instrument-robust inference. In these cases, we show Anderson-Rubin confidence sets alongside raw coefficients and generate multipliers from the minima. For jobs (Table 3), confidence sets show a 10 percent increase in creative jobs causes between 1.12 percent and 6.2 percent more nontradable jobs in UK cities between 1998 and 2018, compared to a 1.2 percent increase in the OLS setting. As before, the overall change is driven by the pre-2007 period.

Multipliers give us a simple alternative heuristic for interpreting our results. While the OLS multiplier is 2.13, the IV multiplier is at least 1.96. This implies that over the period 1998–2018, each urban creative job generates at least 1.96 nontradable jobs (the multiplier drops from 2.48 jobs pre-2007 to 0.8 jobs from 2007). What does this mean in practice? Creative *multipliers* are larger than the cross-OECD average for tradables, which is 0.9 (What Works Centre for Local Economic Growth, 2019).[10] But the creative sector is relatively small (see Table 1), so the *overall effect* of the

[10]Our multiplier of tradable on nontradable activity (0.287) is rather lower than the cross-country average of 0.9 in the What Works Centre review, but rather higher than their minimum of 0.13. US estimates covered in the review range from 0.53 to 1.6.

Table 4

IV Regression for Impact of Creative Workplaces on Nontradables. Long Difference Estimator 1998/2018.

	OLS	IV			
	(1)	(2)	(3)	(4)	(5)
Log creative industries firms	0.30***	0.06	0.07	-0.08	
	(0.092)	(0.105)	(0.084)	(0.127)	
Log other tradable firms	0.65***	0.85***	0.82***	1.02***	
	(0.140)	(0.122)	(0.097)	(0.151)	
Log tradable firms					-0.05
					(0.527)
log TTWA-coalfield distance		*0.13****	*0.15****	*0.12****	
		(0.045)	*(0.046)*	*(0.036)*	
TTWA frequency of art schools		*0.03*	*0.02*	*0.04*	
		(0.064)	*(0.069)*	*(0.056)*	
Log Bartik tradable firms					*0.58**
					(0.328)
Observations	156	156	156	156	156
R^2	0.91	0.97	0.98	0.98	0.59
Kleibergen-Paap *F*-statistic		4.22	5.36	5.44	3.14
Montiel Olea-Pflueger Effective *F*		4.975	5.96	6.176	3.145
Anderson-Rubin confidence set		[0.209, 0.553]	[0.171, 0.383]	[-0.493, 0.364]	[., 0.467]
Multiplier—Van Dijk	2.516	[1.761, 4.657]	[1.438, 3.327]	[-4.076, 3.014]	[., 1.261]

Source: BSD, APS, LFS, ONS datasets.
Note: TTWA-by-year cells. All models use controls as in our main specification. Standard errors in parentheses, clustered on TTWA. * 10%, ** 5%, *** 1% significance. Confidence sets are confidence intervals around point estimates for creative industries jobs, except for column 5 (tradable jobs).

multiplier is modest. The 6,663 creative jobs added in the average UK city between 1998 and 2018 are responsible for 13,020 new nontradable jobs, or 16.4 percent of all nontradable jobs growth during that period. Nevertheless, this is a positive contribution to what is largely a self-fueled nontradable jobs expansion. For workplaces (Table 4) the picture is very different. IV coefficients are smaller, and now all are nonsignificant. Multipliers are also reduced, with all around zero.

These results are robust to alternative estimations pooling across all years (Tables B13–B14 in the online material), to alternative specifications using a shift-share instrument, and to instrumenting for *both* creative and other tradable activity (Tables B15–B16 in the online material). In the latter case, IV estimates are always larger than our main results. Since other tradable activity is also an endogenous variable of interest (see "Research Design"), this is reassuring and implies that we can treat our main results with some confidence.

Overall, our analysis suggests that creative multipliers on nontradables come through the intensive margin—that is, more jobs in nontradable businesses—rather than the extensive margin—more nontradable firms. Creative industries' procyclicality, as discussed in "Theoretical Framework," likely explains why effects die back after the shock of the Great Financial Crisis.

Extensions

We now explore the other two parts of our conceptual framework. We first test for multiplier effects from creative industries to other tradable sectors. Per "Theoretical Framework," these could reflect matching effects through supply chains and/or learning effects through broader urban knowledge spillovers. Next, we decompose our main results for nontradable jobs across creative industry subgroups. This helps explain how nontradable jobs multipliers may operate: worker spending, visitor spending, or both.

Creative Multipliers in Tradable Space

We test links between creative industries activity and activity in other tradables by estimating in long differences, for TTWA i in year t:

$$\Delta ln\mathrm{OT}_{it-tbase} = a + b1\Delta \ln\ \mathrm{CI}_{it-tbase} + b2\Delta \ln\ \mathrm{NT}_{it-tbase} + \Delta Xc_{it-tbase} + \mathrm{T}_t + e_{it} \quad (3)$$

Here, OT is either jobs or workplaces in other tradable manufacturing/services, and other terms and controls are defined as before. Table 5 gives results, using the art school instrument only. Panel A covers jobs and Panel B, workplaces. For each, column 1 gives OLS results, and columns 2–4 give results for 1998–2018, 1998–2006, and 2007–18, respectively.

While OLS results suggest spillovers from creative to other tradable activity, this is noncausal. By contrast, we find no significant results for IV regressions. However, IV estimators are poorly fitted, and confidence sets are empty, implying misspecification (Andrews, Stock, and Sun 2019). Alternative specifications combining the art school and shift-share IVs (for creative or other tradable activity) also almost always yield nonsignificant results.

Overall, we interpret these findings as suggestive, noncausal evidence of spillovers to other tradable activity, noting their consistency with other studies (Müller, Rammer, and Trüby 2009; Pratt and Jeffcut 2009; Boix-Domenech and Soler-Marco 2017). Further research using alternative research designs could confirm the extent and direction of these effects.

Decomposing Creative Job Multipliers

Here we provide exploratory, noncausal evidence on how creative job multipliers may operate on nontradable employment. Per "Theoretical Framework," we can do this by exploring mutlipliers for creative industry subgroups. If these are large and statistically significant in creative services versus arts, this is evidence that multipliers operate through worker spending versus visitor spending, and the converse.

Figure 5 summarizes OLS results and 95 percent confidence intervals for each of the nine DCMS subgroups in turn, for 1998–2006 (left-hand panel) and 2007–18 (right-hand panel). Coefficients represent the relative *effect* of each subgroup, controlling for other creative industries, other tradable activity, with controls and fixed effects as before. Appendix Table B17 in the online material gives full details.

For 1998–2006, we find some evidence for creative service spending power over visitor amenity spending, with robust coefficients for architecture, design, film, and publishing. However, the channel works unevenly, with no robust links for advertising/marketing and IT, two high-wage subgroups. We speculate that this may reflect the former

Table 5

IV Regression of Creative and Other Tradable Activity. Long Difference Estimator 1998/2018

A. Employment	OLS (1)	IV (2)	IV (3)	IV (4)
Log creative industries jobs	0.20*	-0.29	4.93	-0.32
	(0.110)	(1.776)	(102.090)	(2.559)
Log nontradable jobs	0.95***	1.3	-4.73	1.38
	(0.232)	(1.994)	(118.330)	(2.832)
TTWA frequency of art schools		*0.02*	*0*	*0.01*
		(0.076)	*(0.073)*	*(0.067)*
Observations	156	156	156	156
R^2	0.47	0.93	-3.1	0.93
Kleibergen-Paap *F*-statistic		0.06	0	0.05
Montiel Olea-Pflueger Effective *F*		0.06	0.003	0.05
Anderson-Rubin Chi^2		0.0237	0.222	0.0176
Anderson-Rubin confidence set		[.,.]	[.,.]	[.,.]
B. Workplaces	**(1)**	**(2)**	**(3)**	**(4)**
Log creative industries firms	0.22**	0.13	0.12	0.08
	(0.090)	(0.354)	(0.307)	(0.581)
Log nontradable firms	0.70***	0.86**	0.90**	0.92
	(0.074)	(0.415)	(0.365)	(0.670)
TTWA frequency of art schools		*-0.06*	*-0.07*	*-0.04*
		(0.069)	*(0.065)*	*(0.058)*
Observations	156	156	156	156
R^2	0.93	0.98	0.98	0.98
Kleibergen-Paap *F*-statistic		0.81	1.26	0.45
Montiel Olea-Pflueger Effective *F*		0.81	1.26	0.45
Anderson-Rubin Chi^2		0.106	0.141	0.0169
Anderson-Rubin confidence set		[.,.]	[.,.]	[.,.]

Source: BSD, APS, LFS, ONS data sets.
Note: TTWA-by-year cells. All models use TTWA and year dummies, plus controls as in our main specification. Standard errors in parentheses, clustered on TTWA. * 10%, ** 5%, *** 1% significance.

activities' broader upstream entanglements versus the latter's more specialized functions. We also find some support for the amenities channel, with robust coefficients for museums and libraries, and for the arts. Consistent with our overall results, subgroup coefficients get substantially smaller and nonsignificant after 2007, and services versus amenities differences also largely disappear at this point.

Conclusions

Economic geographers have paid much attention to the creative industries, because they cluster in cities (Zukin 1995; Hall 1998; Hutton 2008; Scott 2014), and because they may drive urban growth (Florida 2005; Boschma and Fritsch 2009; Marrocu and Paci 2012). However, evidence on the latter is surprisingly sparse (Bloom et al. 2020). In this article we explore the long-term, causal impacts of the creative industries on surrounding urban economies. Using a new twenty-year panel of UK cities, we directly estimate causal effects of creative on noncreative activity. Given high and increasing urban concentrations of creative activity in many countries (Boix et al.

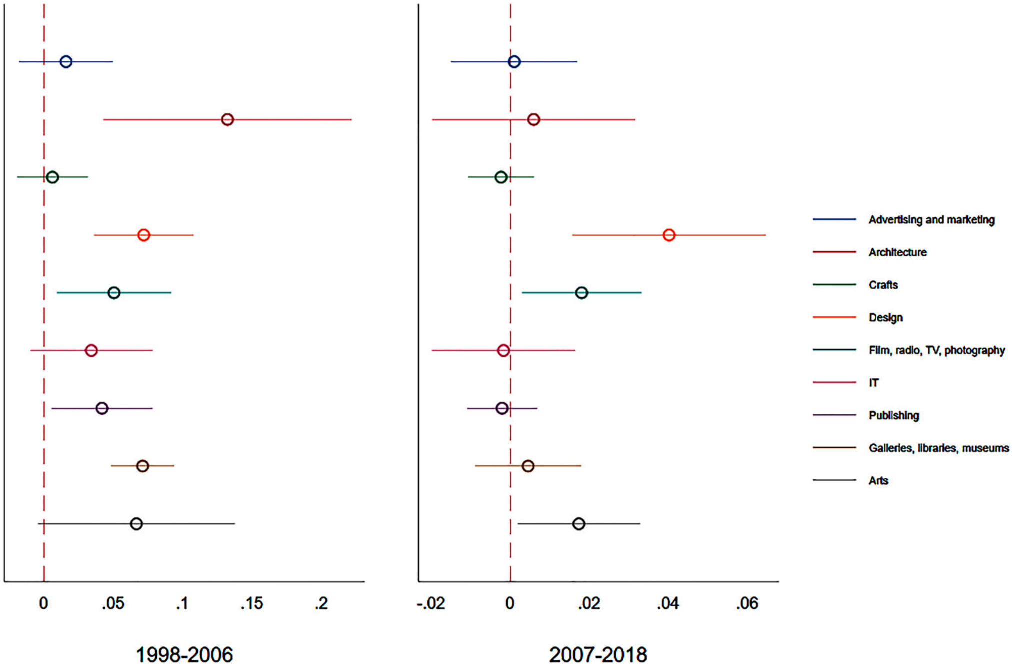

Figure 5. Plot of OLS regression of creative subgroup employment on nontradables.
Note: Each point shows OLS coefficient and 95 percent confidence interval for subgroup, controlling for the rest of the creative industries. All modules use TTWA dummies, plus controls from our main specification.
Source: BSD, LFS/APS, ONS, TTWAs by year cells.

2014; Alfken, Broekel, and Sternberg 2015; Nuccio and Ponzini 2017; Tao et al. 2019), our results hold value beyond the UK setting.

We have four main findings. First, consistent with other recent studies (Boix et al. 2014; Nuccio and Ponzini 2017; Mateos-Garcia, Klinger, and Stathoulopoulos 2018; Tether 2019), we find creative industries activity becoming increasingly clustered in a small number of cities, albeit with diffusion *within* these clusters.

Second, we find significant, positive employment multipliers of creative jobs on surrounding local service employment. In the average city, each creative job adds at least 1.96 nontradable jobs over our twenty-year sample period.[11] Consistent with creative activity being highly procyclical, effects are driven by the pre–Great Financial Crisis period. Given the relatively small size of the creative sector, and the extreme clustering of creative activity, the creative multiplier's overall impact is both modest and uneven. On average, the creative sector is responsible for 16.4 percent of nontradable job growth in 1998–2018, though impacts will be larger in bigger clusters. We find no statistically significant causal impacts for workplaces—which suggests that change is coming from

[11]As discussed in "Data" and "Research Design," we know that creative jobs are likely to be undercounted in our data. In turn, this may overstate our multipliers, given the construction of equation (2). In practice, adjusting for this is unlikely to change our story hugely. For example, if we conservatively assume that we are undercounting true creative employment by as much as 10 percent, our multiplier reduces from 1.96 to 1.73. In turn, this reduces the nontradable jobs effect in the average city from around 12,200 to 11,200 or 13 percent of the nontradable growth during 1998–2018.

the intensive (more jobs in existing nontradable businesses) rather than the extensive margin (more nontradable businesses creating more jobs).

Third, we suggest that multiplier effects are associated with both creative business services employees' local spending and amenity visitor spending, although the former, albeit uneven, outweighs the latter. However, we find both overall and subgroup impacts reducing in the post-2007 era, in line with Lee (2014) and Lee and Clarke (2017).

Fourth, we find weak, suggestive evidence of spillovers to other tradable activities, consistent with Lee (2014), Bakhshi and McVittie (2009) and Boix-Domenech and Soler-Marco (2017) who highlight the impact of creative industries on supply innovation and productivity spillovers.

More broadly, these results may challenge some common perceptions on the effects of creative city policies (Mathews 2010; Lindner 2018) at the urban level. First, such policies will have partial and uneven local economic impacts. Specifically, our results suggest that spatially and sectorally blind, creative-led economic policies are unlikely to be efficient in both addressing regional disparities and maximizing employment growth in specific areas. Rather, any positive effects will be focused on a few large urban areas, with the risk of further exclusion of marginal areas. Second, spillovers likely stimulate existing activities over new businesses, and our strongest evidence points to impacts on local services rather than other high-value tradables. This goes against notions of the creative city as a broad-based urban economic development strategy (Florida 2002). Or to put it more constructively, the extent to which creative industries *specifically* favor further innovative activities and quality jobs still needs to be empirically proved.

Our research has a number of limitations, which open up space for further work. First, our contribution is limited to economic spillovers, neglecting the relevant social effects of the arts, museums, and cultural heritage. Second, we lack worker-firm data so we cannot explore the economic impacts of creative occupations, either inside or outside creative firms (Bakhshi, Freeman, and Higgs 2012). Third, we do not explore within-city change, for example, in specific creative districts or neighborhoods (Hutton 2015). Fourth, we do not consider wider impacts on (for example) the housing market. Finally, we focus on aggregate effects and do not explicitly consider winners and losers, either in terms of firm outcomes or individuals' labor market/life chances. We look forward to future research exploring these spaces.

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